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Accounting for interannual variability in agricultural intensification: the potential of crop selection in Sub-Saharan Africa

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Abstract

Providing sufficient food for a growing global population is one of the fundamental global challenges today. Crop production needs not only to be increased, but also remain stable over the years, in order to limit the vulnerability of producers and consumers to inter-annual weather variability, especially in areas of the world where the food consumed is mainly produced locally (e.g. Sub Saharan Africa (SSA)).

For subsistence agriculture, stable yields form a crucial contribution to food security. At a regional to global scale dynamical crop models can be used to study the impact of future changes in climate on food production. However, simulations of future crop production, for instance in response to climate change, often do not take into account either changes in the sown areas of crops or yield interannual variability. Here, we explore the response of simulated crop production to assumptions of crop selection, also taking into account interannual variability in yields and considering the response of agricultural productivity to climate change. We apply the dynamic global vegetation model LPJ-GUESS, which is designed to simulate yield over large regions under a changing environment. Model output provides the basis for selecting the relative fractions of sown areas of a range of crops, either by selecting the highest yielding crop, or by using an optimization approach in which crop production is maximized while the standard deviation in crop production is kept at below current levels.

Maximizing simulated crop production for current climate while keeping interannual variability in crop production constant at today's level generates rather similar simulated geographical distributions of crops compared to observations. Even so, the optimization results suggest that it is possible to increase crop production regionally by adjusting crop selection, both for current and future climate, compared to assuming the same cropland cover as today. For future climates modelled production increase is >25% in more than 15% of the grid cells. For a small number of grid cells it is possible to both increase crop production while at the same time decreasing its interannual variability. Selecting the highest yielding crop for any location will lead to a large potential increase in mean food production, but at the cost of a very large increase in variability.

1 Introduction

Global food security is a fundamental challenge for Earth's current and future population. Currently around 840 million people in the world are under-nourished (Food and Agricultural Organisation, 2013). Due to an increasing global population and changes in food consumption patterns, it is expected that crop production needs to double by 2050, for which several options exist in principle. On the production side this entails either increasing the extent of agricultural land or increasing production on existing cropland. In this context, reducing the difference between actual and potential yield (closing the so-called yield gap) through improved management (including irrigation and fertilizer use) and by selection of appropriate cultivars (Foley et al., 2011; Licker et al., 2010; Mueller et al., 2012) is fundamental.

A second option, somewhat less discussed, would be to select different crop *species* (as opposed to different cultivars of the same crop) that give a higher yield locally (Franck *et al.*, 2011; Koh *et al.*, 2013). For example, Koh et al. (2013) found that global cereal crop production could increase by 46% when selecting the highest yielding cereal (in terms of mass) for each location. But selecting the highest yielding crop in all locations is not rational if one wishes to ensure stability in the global crop production. Already the risk of an increasing volatility, as a consequence of agricultural systems becoming more homogenous, is being debated, since a few dominating crops can be vulnerable to episodic events such as extreme weather or disease (Khoury *et al.*, 2014). Moreover, in many parts of the developing world, such as in Sub-Saharan Africa (SSA), people are largely dependent on local crop production for their sustenance and lack the means to compensate for years of poor production by buying food on global markets (Devereux and Maxwell, 2001; Funk and Brown, 2009). This means that local crop production is a critical aspect for establishing local food supply (Garrity *et al.*, 2010) but making local population highly vulnerable to the effects of extreme weather events and crop failure. In addition, SSA is also a region where the effects of climate change on agriculture are expected to be most adverse (Barrios *et al.*, 2008; Kotir, 2011), including an increased vulnerability in the majority of the region’s rain-fed cropland area, which constitutes 97% of the total cropland area (Rockström *et al.*, 2004).

In regions where food security is closely linked to local food production, the inter-annual variability in yields also needs to be taken into account. In a changing future climate, one key question is whether farmers in a more variable future climate will still aim to “optimise productivity under increased climate variability or adopt strategies and management practices that are more risk averse, and aim to achieve consistent, but potentially lower, productivity" (Matthews *et al.*, 2013). In theory, crops could thus be selected in order to maximize crop production while keeping interannual variability in production at an acceptable level. Although it must be considered that in reality, other factors also affect the selection of the crops sown, such as food preferences and market drivers.

To study potential future changes in regional to continental and global crop production, large-scale agricultural models have become useful tools for predicting future changes in crop yield over large regions (Berg et al., 2011; Bondeau et al., 2007; Deryng et al., 2011; Di Vittorio et al., 2010; Drewniak et al., 2013; Gervois et al., 2004; Lindeskog et al., 2013; Lokupitiya et al., 2009; Sus et al., 2010; Tao et al., 2009). For example, many of these models have been applied within the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig *et al.*, 2013b) including a model intercomparison study where the effect of global change on future crop yield globally was simulated using a large number of crop models (Rosenzweig *et al.*, 2013a). However, to date most analyses have concentrated on the impact of climate on mean yields, while studies that have also investigated the effect of climate change on changes in yield variability are rare. Despite often being described as tools to support adaptation strategies, relatively few examples of studies in which crop models have been applied to these types of questions can be found in the literature (Webber *et al.*, 2014).

The Modern Portfolio Theory (MPT) (Markowitz, 1959) is a theory within economics for selecting a portfolio of stocks taking into account not only the monetary return of the portfolio of these stocks, but also risk aversion. This has been extended into the realm of agriculture, looking at the return of a portfolio of different crop varieties of wheat and rice (Nalley *et al.*, 2009; Nalley and Barkley, 2010). We broaden this approach here further by combining MPT with simulated yields for SSA from an agrological global dynamic vegetation model (LPJ-GUESS; Smith et al., 2001, Lindeskog et al. 2013). Rather than looking at maximizing financial return we here instead maximize the number of calories produced. In this study we explore the potential to increase crop production through crop selection for SSA while also taking into account interannual variability in production. This study is a stylised experiment, and not intended to represent the decision making of individual farmers, which is determined by many economic aspects beyond climate effect on yields such as food preference, market value, or access to markets.

The focus of the study is the potential increases in crop production that could be attained through crop selection whilst constraining to an acceptable level of variance in production. The increase in production in this study is thus assessed without extending agricultural land or through increased irrigation or fertilizer use.

Using the same acceptable level of crop production for future yield means that this study also takes into account limited climate adaptation. While performing the analysis we generate optimized relative cropland cover for each crop and grid cell.

The main purpose of the study is to:

1) Explore the potential to increase crop production through crop selection for SSA while also taking into account interannual variability in production using simulated yield and an optimization approach.
2) Explore changes in the optimized cropland fractions over time for a range of crops.
3) Compare the optimized geographical distributions of crops to observed distributions for current climate.

2 Methods

Here we use a state-of-the art agrological global dynamical vegetation model LPJ-GUESS (Lindeskog et al., 2013; Smith et al., 2001) to simulate current and future potential crop production in SSA. Simulated yields are then used as the basis for two different optimizations. The first one is to select the single highest yielding crop. The second option is based on MPT and here the relative sown areas for a range of crops are adjusted in order to maximize the number of calories produced while at the same time keeping the variance at a minimum level.

2.1 Model description

LPJ-GUESS is a deterministic, process-based dynamic global vegetation model designed to simulate patterns and dynamics of natural vegetation and corresponding fluxes of carbon and water (Lindeskog et al., 2013; Smith et al., 2001). It is driven by daily temperature, precipitation and short wave radiation and runs at a daily time scale, typically with a spatial resolution of 0.5º. Model processes include photosynthesis, respiration, water uptake, evapotranspiration, and carbon allocation and growth. The model has been evaluated against a broad range of observations, including for carbon fluxes in European forest ecosystems (Morales *et al.*, 2005), seasonality of vegetation greenness in cropland regions in Africa (Lindeskog et al., 2013), interannual variability of terrestrial carbon uptake (Ahlström *et al.*, 2012), CO_2 fertilisation response (Hickler *et al.*, 2008), and yields and soil carbon response after land-use change (Pugh *et al.*, 2015). Cropland processes have been recently introduced into LPJ-GUESS, with crops represented through 11 typologies of crops named Crop Functional Types (CFTs; Bondeau et al., 2007). Carbon allocation to various yield organs depends on summed heat units (degree-days above a crop-specific base temperature), also calculated at a daily time step. A dynamic Potential Heat Unit (PHU) sum needed to reach full maturity is calculated for each grid cell and each CFT based on the mean temperature of the last 10 years (Lindeskog et al., 2013). This approach means that the model assumes that varieties with growing periods adapted to the prevailing climate are always available and selected. As such, it represents the opposite approach to that commonly employed in global crop models of no cultivar adaptation to climate whatsoever (e.g. Rosenzweig et al., 2013). A new sowing algorithm based on Waha *et al.*, (2012) was also introduced where the timing of sowing depends on the variability in temperature or precipitation, rather than being specified from external datasets. Disturbance and mortality through extreme weather, pests and deceases are presently not yet accounted for in crops. Yields of CFTs are simulated separately for irrigated and rain-fed crops. Except for sowing and irrigation, crops are assumed to be grown under similar conditions regarding management, nutrients and pests across all grid cells in the model.

2.2 Modelling crop yield using LPJ-GUESS

Here we used the simulated rain-fed yield from the LPJ-GUESS model runs from the model intercomparison study performed as a part of AgMIP (Rosenzweig *et al.*, 2013b). The model was driven by bias corrected climate forcing data from 5 General Circulation Models (GCMs) (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M) obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive (Taylor *et al.*, 2012). Seven of the LPJ-GUESS CFTs (Table 1) were applied in this analysis for SSA (<15.5 ^{o}N). In this paper we focused on the results using climate data from one Representative Concentration Pathway (RCP 6.0) (Meinshausen *et al.*, 2011) analysing the results for current (1996-2005) and two future climates (2056-2065 and 2081-2090). The RCP 6.0 was selected as this represents one of the "middle of the road" scenarios.

Table 1 List of group of crops, or Crop Functional Types (CFT), included in the study. Listed are also which crops belong to each CFT.

CFT name	**Crops included in CFT**
Temperate Cereals	Winter wheat, Spring wheat, Rye, Barley, Oats
Temperate Maize	Corn/Maize
Temperate Pulses	Beans and other pulses
Temperate Tubers	Potatoes, Sugar beet
Tropical Cereals	Millet, Sorghum
Tropical Rice	Rice
Tropical Tubers	Maniok/Cassava, Sweet potatoes

2.3 Scaling simulated yield to observed values

Since the simulated output from LPJ-GUESS does not account for regional differences in management actions such as fertilisation and pest control, but rather the potential response due to weather/climate and atmospheric CO_2 concentration, simulated yields were first scaled against observed values to correct for this spatial variability. To do this a conversion coefficient (*k*) representing the difference in simulated and reported yield was first calculated for each CFT (c) and grid cell (*i*):

$$k_{i,c} = 1 - \frac{Y_{o,i,c}}{Y_{p,i,c}} \qquad (1)$$

where $\overline{Y_p}$ is mean simulated yield (Y_p) (kg m^{-2} dry weight) for the current time period (1996-2005) and Y_o, is actual yield (kg m^{-2} dry weight) foe the same time period. Observed yields (Y_o) were taken from the Spatial Production Allocation Model (SPAM) dataset (You *et al.*, 2013). The SPAM dataset is a gridded product of crop yield and area compiled from a range of datasets centred at the year 2000 and disaggregated to a 5 arc-minute spatial. As the spatial resolution of LPJ-GUESS is 0.5° we aggregated the SPAM dataset to that same spatial resolution. Also, as SPAM reports wet weight, the yields were converted into dry weight using crop specific values for grain/tuber water content (Wirsenius, 2000). SPAM reports yield separately for high and low input of nutrients as well as subsistence farming. As subsistence farming can be said to be dominating for most parts of SSA and as this type of farming is also the focus of this study, subsistence yields were selected to represent observed yield in this study. For CFTs representing more than one crop, we selected the crop giving the highest dry yield from the database. This represents a form of optimization in itself where yield is maximized within each CFT containing more than one crop. In order to avoid getting unrealistically large or small values of k we excluded CFTs (c), in a grid cell (i) from this analysis if either observed (Y_o) or mean simulated yield ($\overline{Y_p}$) were zero or close to zero (<0.01 kg dry weight m^{-2}). For these CFTs we instead assigned k a "gap-filled" value (k_{gap}) based on a distance weighted interpolation using yield data from grid cells that were within the same agro-ecological zone (AEZ) (Fischer *et al.*, 2012):

$$k_{gap,i,c} = \frac{\sum_{j=1}^{n} \frac{k_{j,c}}{d_{i,j}}}{\sum_{j=1}^{n} \frac{1}{d_{i,j}}} \qquad (2)$$

where $d_{i,j}$ is the distance (in degrees) between cell i (the grid cell for which k_{gap} is calculated) and any cell j which has existing values of k for CFT (c), belonging to the same AEZ as grid cell (i), and is within a 2.5° distance from i. In the case no k values could be found within 2.5° from grid cell i k_{gap} was set to 1.0.

Simulated scaled annual yield (Y_s) in kg m^{-2} dry weight for each year was calculated using simulated yield (Y_p) and the conversion coefficient (k) for each CFT (c), grid cell (i) and year (t):

$$Y_{s,c,i,t} = Y_{p,i,c,t}(1 - k_{i,c}) \qquad (3)$$

Y_s was converted from kg m^{-2} to kcal m^{-2} (Y_{cal}) (1 kcal = 4184 J) by using values for calorie content for each crop from the Food and Agricultural Organization (FAO) (2001) as suggested by Franck *et al.* (2011).

2.4 Observed CFT fractions

Total observed areas for each crop were also taken from the SPAM dataset. (You *et al.*, 2013). In contrast to yields, this dataset contains only the *total* cropland area for each crop rather than separating areas into different types of management and including both rain-fed and irrigated crops. Observed CFT fractions (ω_o) were calculated as the summed area of each CFT, divided by the total area of the 7 CFTs within each grid cell for all cells with at least one CFT present. For example, if three CFTs were present the fraction for one of these was calculated as the area of that CFT divided by the summed area of all three CFTs.

2.5 Modern Portfolio Theory

The approach in this study using Modern Portfolio Theory (MPT) (Markowitz, 1959) was based on Nalley *et al.* (2009); and Nalley and Barkley (2010) but instead of optimizing variance in yield or profit from selecting different varieties of wheat or maize the focus was on optimizing crop production by selecting different crop species.

The two variables used in MPT are the mean return of the portfolio, or in the case for crops in this study, the area weighted mean yield for the total cropland area in each grid cell over the selected time period (Y_{pf} in kcal m^{-2}), and the variance (σ^2_{pf} in kcal^2 m^{-4}) in the same yield over the same time period. Y_{pf} was calculated as the area-weighted decadal mean yield of all CFTs in each grid cell (*i*), for each optimization period:

$$Y_{pf,i,t} = \frac{\sum_{t=1}^{a} \sum_{e=1}^{b} \omega_e Y_{cal,e,t}}{a} \quad (4)$$

where *t* is year number in the optimization period, *e* is the CFT index (a number between 1-7 where each number represents one CFT), *a* is number of years of the optimization time period, *b* is number of CFTs, and ω_e is the cropland fraction of CFT *e*.

The portfolio mean variance ($\sigma^2{}_{pf}$) is the area-weighted sum of the variance in crop yield calculated as:

$$\sigma^2{}_{pf,i,t} = \sum_{e=1}^{b} \sum_{f=1}^{b} \omega_e \omega_f \rho_{e,f} \quad (5)$$

where *e* and *f* are CFT indices used in the equation to represent all combinations of CFTs. The variable ρ is the covariance in crop yield of the two corresponding CFTs over the optimization period when $e \neq f$ and the variance of CFT *e* (or *f*) when $e=f$.

Modern Portfolio identifies two optimization options based on the variables described in Eq. 4 and 5. The first option (A) is to find an optimum portfolio of crops to maximize crop production (Y_{pf}) while keeping standard deviation (σ_{pf}) below a maximum value. The second option (B) is to find the optimum portfolio of crops to minimize standard deviation (σ_{pf}) while keeping crop production (Y_{pf}) above a minimum value. This type of optimization problem needs to be solved numerically. In this study we used the optimization tool implemented in the Financial Toolbox in Matlab (release 2013b) (MathWorks Inc., 2013). The Matlab script uses standard deviation (σ) rather than variance (σ^2) in the optimization, and as this measure is easier to relate to for most readers we use this in both the analysis and the presentation of the results. In addition to the thresholds for Y_{pf} or σ_{pf} the optimization algorithm requires an initial state of cropland fractions.

As Y_{pf} is the area weighted yield of all crops and since the total cultivated area of crops does not change over time for any grid cell, maximizing Y_{pf} for any grid cell also means maximizing the number of calories produced for that grid cell and we therefore use Y_{pf} as a measure of crop production for any grid cell *i*.

2.6 Maximizing crop production through crop selection

In order to study the impact of crop selection for maximizing crop production we performed two optimizations per time period (current climate: 1996-2005 and the two future time periods: 2056-2065 and 2081-2090), GCM and grid cell where the first is based on MPT:

Low risk (LR)

Here the first MPT optimization option (A) was used, that is to maximize Y_{pf}, while keeping σ^2_{pf} below a maximum threshold. This optimization represents a low risk scenario where the interannual variability in crop production is not allowed to be higher than simulated crop production using current cropland cover. The value of this threshold is calculated using Eq. 5, based on simulated Y_{cal} values for the current time period (1996-2005) and assuming current observed cropland fractions (as described above). The optimization was made for all CFTs that are currently grown in a given grid cell according to the SPAM dataset. The initial state for the cropland fractions (ω) for all CFTs in the optimization was assumed to be equal to the observed fractions (ω_o). Although the optimization is made at a grid cell level this optimization could be seen as a risk aversion strategy for a farmer in a region with local markets and high level of local sustenance.

High risk (HR)

As a comparison to the LR scenario we also selected the highest yielding CFT (in calories) of the ones that are currently growing in each grid cell. Crop production for that grid cell is thus equal to the yield of the highest yielding CFT. This optimization represents a high risk scenario where the crop production is maximized without taking into account climate-related interannual variability in productivity. This optimization is more closely related to commercial agricultural systems where one bad harvest one year can be compensated for by large harvests in “typical” years.

The optimizations were made separately for each GCM. The results below are presented as the mean of all five GCMs.

3 Results

3.1 Optimized CFT fractions

By performing the two optimizations for current climate we generated different sets of optimal CFT fractions (ω_{opt}) for each grid cell, optimization and time period. The unweighted grid cell mean ω_{opt} values for current climate were compared with the observed fractions (ω_o) taken from the SPAM dataset (Fig. 1). This comparison could at least partly be seen as a form of validation, in a sense that it if these patterns agree there is an indication that current cropland cover to some extent follows the assumptions in the optimization. The ω_{opt} values from the LR optimization were relatively similar to the ω_o values, whereas for HR ω_{opt} differed greatly from ω_o, with Tropical Tubers being the dominating crop in the simulated case, covering nearly 60% of the crop area, rather than the ca. 20% observed (Fig. 1). For LR some differences can be seen for Temperate Maize, Temperate Pulses, Temperate Tubers and

Tropical Tubers where grid cell mean ω_{opt} for Temperate Maize and Temperate Tubers was larger than ω_o and smaller than ω_o for Temperate Pulses and Tropical Tubers (Fig. 1)

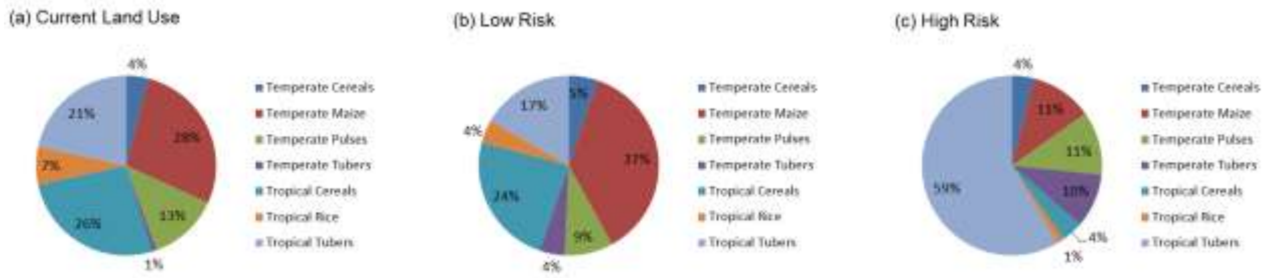

Figure 1. Current grid cell mean CFT fractions (a) as well as optimized CFT fractions (Low Risk: (b) and High Risk: (c)) for current climate.

Latitudinally, both ω_o and ω_{opt} (LR and HR) for the three most important groups of crops in SSA (based on number of calories produced (FAOSTAT)) varied strongly (Fig. 2) with the latitudinal fraction for LR reproducing the data-based observed patterns quite well. A strong positive correlation ($p<0.001$) was found between the latitudinal mean values of ω_o and ω_{opt} for the LR-optimization (Table 2) for all CFTs except for Tropical Rice, indicating that current crop selection is close to optimum calculated based on the LR scenario. As correlation does not take into account the bias between predicted and observed values, the Modelling Efficiency (ME) (Janssen and Heuberger, 1995) was also calculated (Table 2). A negative ME value indicates a very poor fit whereas a value close to unity indicates a good fit. Of the CFTs with significant correlations between ω_o and ω_{opt} the ME values were positive for all CFTs except for Temperate Pulses and Temperate Tubers (Table 2).

For the HR scenario the latitudinal pattern of ω_{opt} differed greatly from that of ω_o for all CFTs (Fig. 2 and Fig. S1). Still, there was a significant correlation ($p<0.001$) between ω_o and ω_{opt} for Temperate Pulses, Temperate Tubers, Tropical Tubers and Tropical Cereals (Table 2).

However, looking at the ME, none of the CFTs generated positive values, indicating a poor fit between ω_o and ω_{opt}. The ME values was smaller for HR compared to LR for all CFTs.

Table 2. Pearson's correlation (R) and Modelling Efficiency (ME) between observed and optimized latitudinal CFT fractions (High or Low Risk) of cropland cover for all Crop Functional Types (CFTs). Significant correlations (p<0.001) and positive values for ME are marked in bold.

CFT	**Low Risk (LR) Scenario**		**High Risk (HR) Scenario**	
	R	ME	R	ME
Temperate Cereals	**0.91**	**0.81**	-0.09	-0.15
Temperate Maize	**0.61**	**0.26**	0.03	-2.01
Temperate Pulses	**0.42**	-0.48	**0.35**	-1.82
Temperate Tubers	**0.34**	-5.67	**0.69**	-297.14
Tropical Rice	0.26	-0.39	0.02	-1.25
Tropical Tubers	**0.92**	**0.70**	**0.81**	-4.49
Tropical Cereals	**0.84**	**0.65**	**0.59**	-0.49

For the LR optimization some regions stood out in relation to where ω_{opt} of CFTs differed from ω_o. The ω_{opt} values were much higher than the ω_o for Tropical Cereals in the regions south of 25°S; and for Temperate Tubers in the regions around 10°S (Fig. 2 and Fig. S1). For Tropical Rice, ω_{opt} was much lower than ω_o for the region between 15 and 25°S (Fig. S1).

When performing the optimizations for future climate, ω_{opt} differed only to a relatively small degree in absolute terms compared to the optimizations made for current climate. The largest difference in relative fractions between 2081-2090 and 1996-2005 was a decrease by nearly 50% for Tropical Tubers (LR) and Temperate Maize (HR) (Fig. S1).

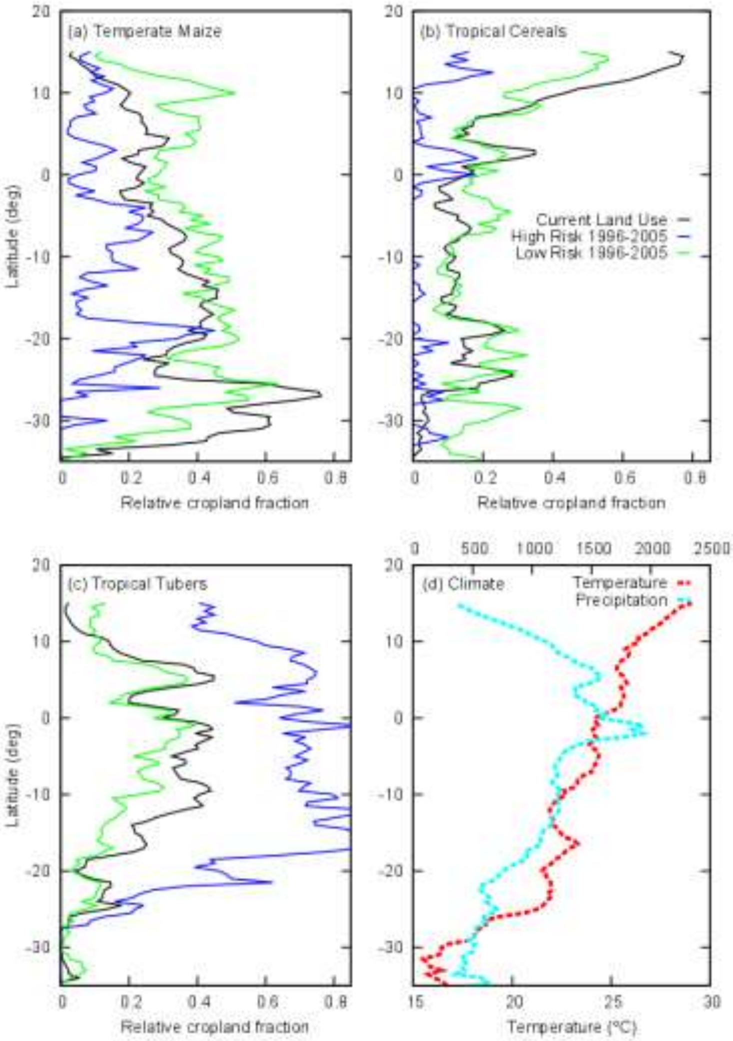

Figure 2. Optimized latitudinal mean CFT fractions for the current climate (1996-2005) (High Risk solid blue lines; Low Risk solid green lines) and observed CFT fractions (black lines) for the three most common crops in SSA: Temperate Maize (a), Tropical Cereals (b), and Tropical Tubers (c). The bottom right panel (d) represents latiudinal mean total annual precipitation (mm) (dotted cyan line) and mean annual temperature (°C) (dotted red line).

3.2 Spatial and temporal differences in crop production and its interannual variability

For future climate we compared the optimized crop production and its standard deviation against a "business as usual" situation which assumed the same CFT fractions as today ($Y_{pf,BAU}$ and $\sigma_{pf,BAU}$). Optimized crop production and its standard deviation were therefore compared against Y_{pf} and σ_{pf} calculated using simulated values of Y_{cal} for current (1996-2005) or future (2056-2065 and 2081-2090) climate, maintaining current observed cropland fractions (ω_o).

3.2.1 Current cropland cover: Business as usual (BAU)

The grid cell median annual value of $Y_{pf,BAU}$ for current climate was 380 kcal m^{-2} with a median value for $\sigma_{pf,BAU}$ of 45 kcal m^{-2} (Fig. 3). Reflecting simulated yield increases in the future, a result mostly in response to enhanced atmospheric CO_2 levels (Rosenzweig et al., 2013), there was an increase in $Y_{pf,BAU}$ over time (Fig. 3a; Fig. S3a-b). From 1996-2005 to 2081-2090 there was an increase in the grid cell median $Y_{pf,BAU}$ by 30%. For the majority of the grid cells (~65%), there was also an increase in $\sigma_{pf,BAU}$, leading to an increase in grid cell median $\sigma_{pf,BAU}$ over time (Fig. 3b) of around 15%.

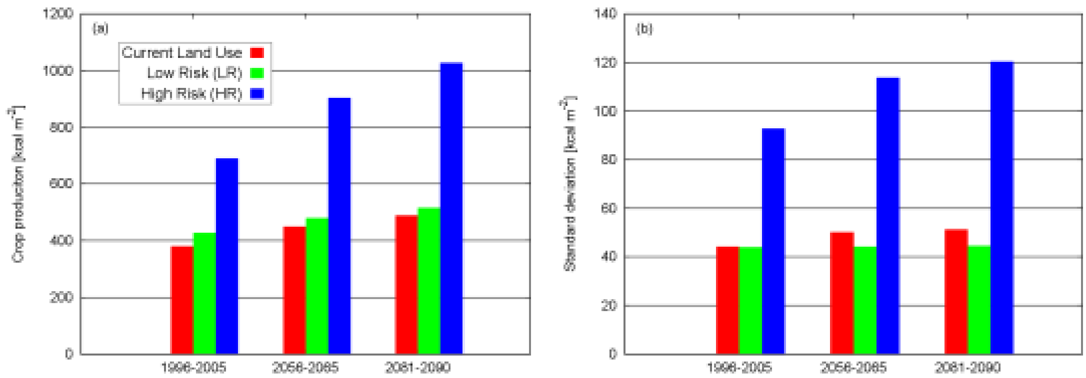

Figure 3. Grid cell median crop production (kcal m^{-2}) (a) and standard deviation (b) (kcal m^{2}) for current (BAU) and optimized CFT fractions.

Geographically, the largest increases in $Y_{pf,BAU}$ over time occurred in Somalia, Botswana and South Africa (Figure S3a-b). The largest increase in $\sigma_{pf,BAU}$ occured in the same regions but also for large parts of West Africa and Sudan (Figure S3c-d). For some regions (e.g. large parts of South Africa and Angola) $\sigma_{pf,BAU}$ instead decreased over time (Figure S3c-d) .

3.2.2 The High Risk Scenario (HR)

Selecting the highest yielding crop (HR) meant that for current climate, optimized Y_{pf} was by definition equal to or higher than $Y_{pf,BAU}$. The grid cell median Y_{pf} was ~70% higher than the grid cell median $Y_{pf,BAU}$. Optimized Y_{pf} was >25% larger than $Y_{pf,BAU}$ for ~80 % of the grid cells for both current and future climate (Table 3; Fig. S4). The grid cells with the highest potential to increase crop production through selecting the highest yielding CFT are mainly located in the Sahel, Angola and in the South Eastern parts of Africa (Fig. S4). The associated σ_{pf} was also much higher than $\sigma_{pf,BAU}$ for the majority of grid cells (with a difference >25% for ~80% of the grid cells: Table 3) and with the median value for σ_{pf} being 110% larger than $\sigma_{pf,BAU}$ (Fig. 3b). For a small number of grid cells (for current and future climate) selecting the single highest yielding crop actually produced a σ_{pf} that was smaller than $\sigma_{pf,BAU}$ (Fig. S5). But the number of grid cells where this difference was larger than 25% was less than 1% of the total (Table 3).

3.2.3 The Low Risk Scenario (LR)

For current climate, the set of assumptions made in LR meant that optimized Y_{pf} was larger than $Y_{pf,BAU}$ across the entire simulation domain, with the grid cell median value being ~12% larger than $Y_{pf,BAU}$. There was an increase over time in the grid cell median optimized Y_{pf} (Fig. 3a), but as the increase in $Y_{pf,BAU}$ was even larger, the relative difference of the grid cell median optimized Y_{pf} and $Y_{pf,BAU}$ became smaller for future climate (~5% for 2081-2090).

Patterns of change were spatially very variable. The largest potential to increase Y_{pf} whilst keeping a σ_{pf} at current level could be found in Senegal, parts of the Sahel, Tanzania, Angola and parts of Mozambique and South Africa (Fig. 4a-c). In total ~10% of the grid cells displayed a Y_{pf} that was at least 25% above $Y_{pf,BAU}$ for current climate, and 16-20% for future climates and CO_2 (Table 3). Following the assumption that the optimization is made against $\sigma_{pf,BAU}$ values for current climate, and the fact that $\sigma_{pf,BAU}$ increases over time for some grid cells, optimized Y_{pf} actually became lower than $Y_{pf,BAU}$ (Fig. 4b-c) for future climates. These grid cells are mainly located in regions where $\sigma_{pf,BAU}$ in crop production displayed the largest increase over time (Fig. S3c-d). For ~5% of the grid cells optimized Y_{pf} was more than 25% below $Y_{pf,BAU}$ for future climates (Table 3).

Table 3. Percent of grid cells where the optimized crop production (or standard deviation) is at least 25% larger (or smaller) compared to using observed CFT fractions (BAU) for the two optimizations and three time periods.

	Low Risk (LR) Scenario			**High Risk (HR) Scenario**		
	1996-2005	2056-2065	2081-2090	1996-2005	1996-2005	1996-2005
Grid cells with increase in yield >25%	9%	16%	20%	77%	80%	81%
Grid cells with increase in yield >25%	0%	4%	7%	0%	0%	0%
Grid cells with increase in standard deviation >25%	0%	5%	7%	80%	82%	83%
Grid cells with decrease in standard deviation >25%	<1%	18%	24%	<1%	<1%	<1%

Following the optimization criteria, optimized grid cell median σ_{pf} changes little over time (Fig. 3b) and for current climate σ_{pf} was smaller than or equal to $\sigma_{pf,BAU}$ for all grid cells (Fig. S6a). Even if there was virtually no change in optimized σ_{pf} over time in absolute terms, the change could be either positive or negative in relative terms compared to $\sigma_{pf,BAU}$. This resulted in optimized σ_{pf} being at least 25% higher than $\sigma_{pf,BAU}$ for ~5% of the grid cells and at least 25% lower for ~20% of the grid cells (Table 3) for future climates. The highest potential to decrease σ_{pf} can be found in western Africa whereas the largest increase in the relative difference of σ_{pf} compared to $\sigma_{pf,BAU}$ can be found in the Sahel, Angola and parts of Mozambique and South Africa (Fig. S6).

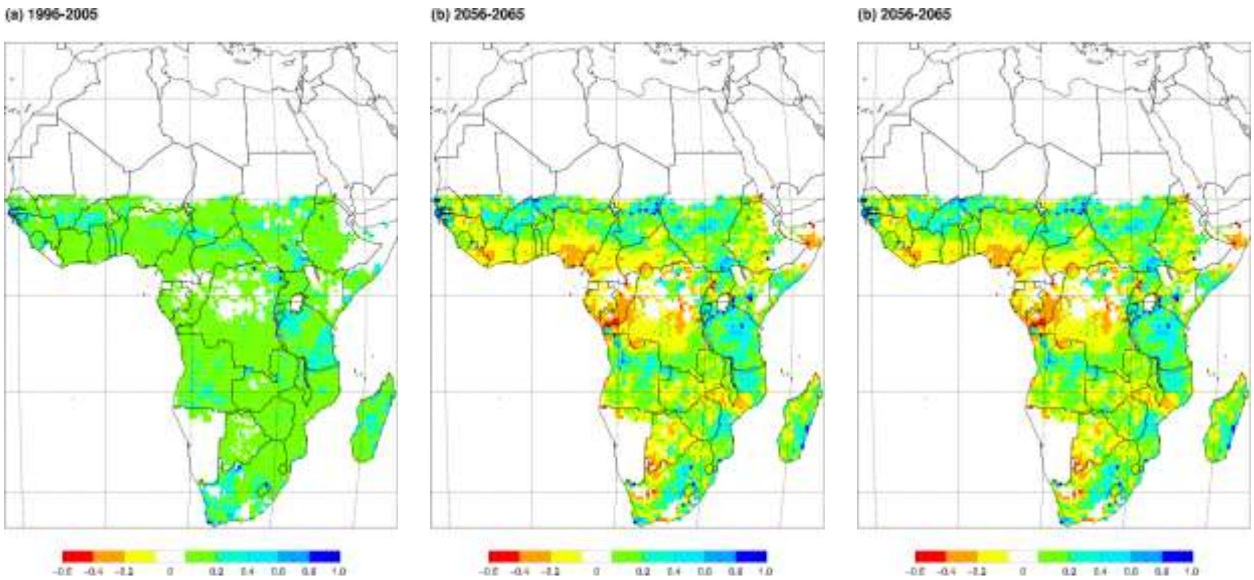

Figure 4. Relative difference in optimized crop production compared to assuming current land use fractions (BAU) for the Low Risk optimization for the time periods:1996-2005 (a), 2056-2065 (b) and 2081-2090 (c).

From the results above (Table 3) it can be seen that for LR, it was potentially possible to simultaneously increase Y_{pf} by 25% and to decrease σ_{pf} by the same figure for the two future time periods compared to the business as usual scenario ($Y_{pf,BAU}$ and $\sigma_{pf,BAU}$) for a number of grid cells. However, the number of grid cells for which both these criteria were met was <1%. If instead looking at the possibility to increase Y_{pf} by 10%, whilst decreasing σ_{pf} by the same magnitude, the number of grid cells for which this occurred increased to ~7%. The grid cells for which it is possible to increase Y_{pf} while at the same time decreasing σ_{pf} are mainly located in the eastern parts of SSA (Fig. S7).

4 Discussion

The agreement between observed and simulated relative cropland cover of the LR optimisation for present-day suggests that cropland cover depends on both yield and interannual variability in yield in a way that makes it possible to recreate the existing spatial patterns for a range of CFTs using simulated yield with LPJ-GUESS and MPT. This pattern relies on assuming simulated interannual variability in crop production of current CFTs as the acceptable level. This agreement is remarkable and implies that in SSA under present-day conditions, crop selection with respect to calorific value is relatively optimal on average, accounting for given interannual variability in weather. Both temperature and precipitation vary notably with latitude (Fig. 2). As climate is the main driver of which CFTs are favoured regionally both in reality and in the optimization it is not surprising that there is a strong correlation between the relative sown areas of CFTs and climate (Table S1). For the observed fractions the strongest correlation with climate was found for temperature for all CFTs (with negative correlations for Temperate Maize, Temperate Tubers and Temperate Cereals) except for Tropical Tubers where the strongest correlation was with precipitation. The correlation between the optimized CFT fractions and climate for LR were of the same direction and order of magnitude for all CFTs except for Temperate Maize. The lack of correlation for Temperate Maize follows a larger optimized fraction in the Sahel compared to the observed (Fig. 2).

The optimizations were made under the assumption that all crops were rain-fed. The reported areas used in this study do however also include some irrigated crops. While for most crops the irrigated area is negligible in SSA, for the two countries with the highest rice production (Nigeria and Madagascar) 15% and 50% of all harvested area is irrigated, respectively (Balasubramanian *et al.*, 2007). This could explain the large underestimation in optimized fractions of rice (Tropical Rice) for the region between 17 and 25°S where Madagascar is located. Furthermore, the CFTs in LPJ-GUESS are not affected by pests, such that yields respond to climatic, but not biotic stresses. This might play a role particularly for potatoes (Temperate Tubers) for which a large amount of pesticides are required compared to other crops in order to protect against, for example, late blight, a fungus responsible for large yield losses in unsprayed fields (Sengooba and Hakiza, 1999) with reported yield losses in central Africa of more than 50% (Oerke, 2006). The expense of these pesticides could partly explain the difference between optimized and observed Temperate Tubers cover.

In the regions south of 25 ^{o}S the LR optimization generated larger fractions of Tropical Cereals than the observed and lower fractions of Temperate Maize. These latitudes are dominated by South Africa, a country where commercial agriculture is practiced on 86% of total cropland (Anon., 2012). By contrast, our study addresses subsistence farming which is the dominating form of agriculture in SSA, and the optimization assumptions are that two important features of agriculture are to maximize the number of calories produced and to ensure a stable production. Other drivers such as maximization of profit (rather than the number of calories), or national to local policies were thus not considered. Regional differences in these drivers could explain the lack of agreement in non-subsistence regions.

Given the overall strong correlation between observed and optimized crop fractions for current climate, the optimizations made for future climate could be seen as scenarios of changes in crop fractions in regions where agriculture is focused on local sustenance. These types of scenarios could be alternatives to assuming no change in land use and crop fraction which is frequently done in impact studies that focus on changes in yields (Liu et al., 2008; Müller et al., 2010; Rosenzweig et al., 2013a; Schlenker and Lobell, 2010). Earlier studies looking at trends in crop selection have mostly done so from the perspective of societal demand for various crops (e.g. Wu *et al.*, 2007). Our study instead focus on the supply side but taking into account also aspects of crop production stability, thus offering a complementary alternative to demand-driven study designs.

For the HR scenario we identified the single-highest yielding crop of each grid-cell for current and future climate (You *et al.*, 2013). By contrast to Tropical Tubers in our study, Franck *et al.,* (2011), using the model LPJmL, found the highest simulated yield for Temperate Tubers (in their study named sugar beet) followed by Temperate Maize. The chief reason for these differences is likely that Franck et al (2011) computed maximum (potential) yield by assuming agricultural intensification, and did not scale simulated yield against observed (actual subsistence) yield as we did for our optimizations. In the study by Koh *et al.,* (2013) the highest yielding cereal (choosing between barley, maize, millet, rice, sorghum and wheat) for each 5 min grid cell was selected based on yield data from Monfreda *et al.,* (2008). Their results gave an increase in crop production by 68% in eastern Africa and 87% in central Africa when selecting the highest yielding crop compared to current crop fraction. The relative increase in production from selecting the highest yielding crop in their study is lower than the one found in our study (HR). Their study however was confined to cereals and also did not take into account any difference in dry weight and calorific contents of the different crops. Moreover, in their study, some crops would be grown under intensive farming whereas our study compared yield of crops grown under today's existing management practices (subsistence farming). Neither of the above studies (Franck et al., 2011; Koh et al., 2013) therefore compare to our HR approach. Regardless of different approaches to estimate increases in crop production, as can be seen from our results, selecting the highest yielding crop generated not only a large increase in crop production compared to current crop fraction but also an even larger increase in interannual variability.

By contrast to the HR approach, in the LR optimization, we investigated the ability to increase yield for a portfolio of crops while keeping standard deviation in crop production constant at the current level. We performed the analysis at the grid scale discussing the potential to increase crop production at regional to continental scale, in contrast to previous work that applied MPT for the selection of crop varieties more locally (Nalley *et al.*, 2009; Nalley and Barkley, 2010). For a range of experimental sites in Arkansas, USA the potential to increase profit in rice production was up to 23% while keeping its standard deviation constant (Nalley *et al.*, 2009). Applying this method for different crop species rather than varieties of rice and for a larger spatial area we find that it is possible to regionally increase crop production by a similar figure.

A commonly discussed option for increasing crop production is the closing of the so-called yield gap (Foley et al., 2011; Licker et al., 2010) through agricultural intensification, which has been estimated for large parts of SSA to lead to yield increases of existing crops by a factor of ~10 (Licker *et al.*, 2010). There are however large obstacles for increasing yields in this manner due to high costs of fertilizers and pesticides, and lack of surface water for irrigation, all of which would need to be applied (Mueller *et al.*, 2012). Switching from one mix of crops to another to maximize crop production whilst keeping an acceptable level of standard deviation in crop production, as suggested by this study, could therefore be seen as an additional option to be explored to produce more calories as well as decreasing the variability in the food production system. Ultimately, what is being sown is determined by the individual farmer and these decisions are affected by the demand for crops locally that may or may not reflect the suitability of those crops in the region.

It is necessary, however, to consider that from a food security perspective many other factors than the generation of a large and/or stable number of calories are equally important, such as access to markets and the nutritional quality and safety of food (Food and Agricultural Organisation, 2013). Not getting enough calories is only one aspect of the food security problem. Micronutrient deficiency is a large problem with an estimated 2 billion people being affected (Tulchinsky, 2010). Also, at the same time as many people still suffer from malnutrition, obesity is a growing problem in the developing world (Godfray and Garnett, 2014; Steyn and Mchiza, 2014) meaning that people simultaneously can be both nutritionally undernourished and obese. Our study focused on staple crops but for a fully nutritional diet these foods need to be complemented by foods which may be richer in minerals, vitamins and proteins (DeClerck *et al.*, 2011). For example, a maize based diet increases the risk for the skin disease pellagra generated by vitamin B_3 deficiency (Hegyi *et al.*, 2004).

By extending the simulations to future climate we simulated changes in yield taking into account not only mean yield changes in future climate but also in its interannual variability. Our projected crop production rates were compared against the “business as usual”-scenario in which cropland fractions were assumed to be the same as today (a common assumption in most modelling studies) and our results can thus be interpreted to consider some degree of climate change adaptation. Model impact studies have traditionally focused on changes in mean yield, ignoring the effect on interannual variability in yield. Those studies that assessed changes in future interannual variability in yield (Chavas *et al.*, 2009; Urban *et al.*, 2012) concentrated on a single crop species. Here we take these approaches a step further, looking at the interannual variability of the total crop production and not only of single crops. Our results indicate that across large parts of SSA crop selection could generate increased future crop production using the same total sown areas as today without increasing the interannual variability in crop production (Fig. 4b-c). Some regions can also be identified where it is possible to both increase crop production and to decrease interannual variability at the same.

Regions not suitable for growing crops today might become suitable in a changing climate. The option to increase crop production by extending crops to new regions was however beyond the scope of this paper as it would require additional analysis on potential and estimated actual yields in regions where crops are currently not growing.

AgroDGVMss, such as the LPJ-GUESS model used in this study, have the advantage of being able to simulate changes in crop production and its standard deviation over large regions and for long time periods (Bondeau et al., 2007; Drewniak et al., 2013; Lindeskog et al., 2013; Rosenzweig et al., 2013a), and furthermore being based on fundamental process-representations of plant physiology, rather than extrapolations of empirical relationships beyond their windows of validity. These advantages come at the price of a lack of spatial detail and therefore several generalizations have to be made (related to e.g. soil types, local climate and crop management, and the effect of heat stress) (Challinor *et al.*, 2009). There are also substantial uncertainties related to model input. Earlier evaluation tests for Africa have however shown the ability of LPJ-GUESS to reproduce interannual variability in yields at the country level as reported by the FAO (Lindeskog et al., 2013) when applying climate input based on observations. Our analysis here was made using bias corrected climate data from 5 GCMs and the mean results from these model runs were used. Simulated fluxes of carbon using LPJ-GUESS have been shown to be highly sensitive to the choice of GCM (Ahlström *et* *al.*, 2012). By contrast to simulated current yield, the standard deviation in yield was not scaled against measured data as the availability of data in the SPAM database for evaluating interannual variability in yield is limited. One potentially useful dataset in this regard is the one recently created by Iizumi *et al.,* (2014) which combines reported data of harvested area for the year 2000, country yield statistics and satellite-derived net primary production into a spatio-temporal gridded dataset of yield for a range of crops. However, two issues prevent comparison of simulated yield against this dataset, grid by grid. Firstly the dataset shows clear differences in interannual variability between grid cells on opposite sides of political borders, i.e. yield dynamics are influenced by the reporting of national yields. Secondly, the climate input data used in this study was based on GCM model runs which cannot represent the actual time-series of climate variability for an individual grid.

In conclusion this study presents a novel approach for simulating the (climate-constrained) potential to optimize crop selection in order to increase food production but at the same time keeping a maximum level of interannual variability in crop production. The close reproduction of the observed latitudinal fractions of most crops in the study implies that, assuming current level of variability in crop production as the acceptable level, agriculture is relatively close to the optimum for producing the highest number of calories. Even so, our results imply that for some regions it is possible to increase the number of calories produced. Based on extending the optimization to future climate assuming the same acceptable level of variability in crop production, increasing regional food production appears plausible. Thus the method demonstrated herein could be seen as a way to introduce climate adaptation into the simulations of future crop production.

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Supplementary

Table S1. Pearson's correlation between the latitudinal mean of observed (OBS) or optimized (High or Low Risk) cropland cover and mean annual temperature (Tair) or total annual precipitation (Prec). Significant correlations ($p<0.001$) are marked in bold. Colours indicate degree of correlation as indicated by the colour bar below.

	Tair			**Prec**		
CFT	*OBS*	*Low Risk*	*High Risk*	*OBS*	*Low Risk*	*High Risk*
Temperate Cereals	**-0.72**	**-0.80**	0.16	**-0.50**	-0.55	0.04
Temperate Maize	**-0.60**	0.05	0.21	-0.26	0.16	0.06
Temperate Pulses	**0.37**	-0.08	**0.52**	0.19	-0.32	-0.17
Temperate Tubers	**-0.65**	**-0.36**	**-0.87**	**-0.36**	-0.04	**0.81**
Tropical Cereals	**0.71**	**0.53**	**0.36**	-0.10	-0.22	**-0.66**
Tropical Rice	**0.38**	**0.39**	0.19	0.25	**0.45**	-0.06
Tropical Tubers	**0.43**	**0.54**	**0.68**	**0.88**	**0.87**	0.29

Tair/Prec	|r|	0.0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	>0.8

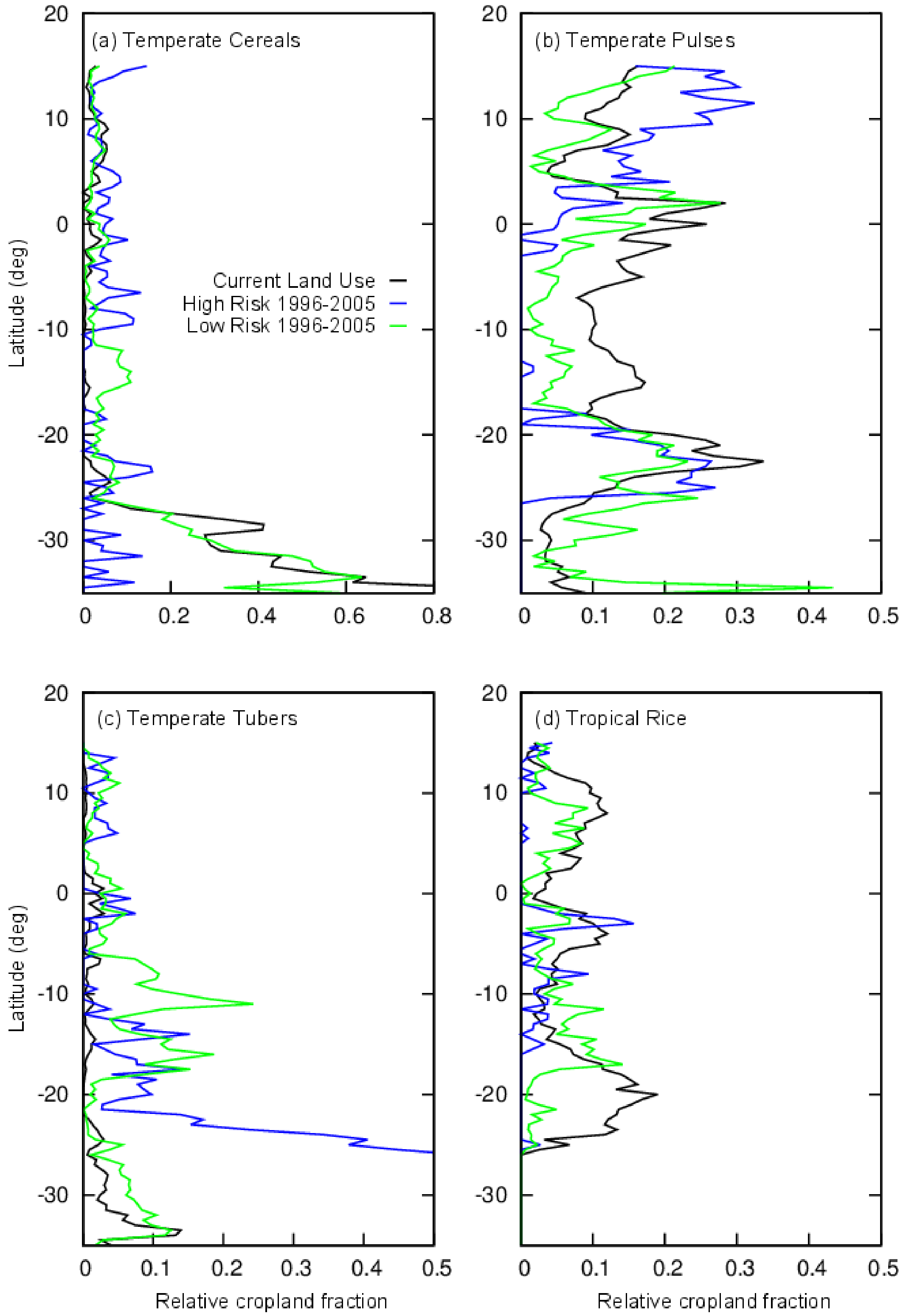

Figure S1. Optimized latitudinal mean CFT fractions for current climate (1996-2005) (High Risk solid blue lines; Low Risk solid green lines) and observed CFT fractions (black lines) *for: Tropical Rice (a), Temperate Cereals (b), Temperate Tubers (c) and Temperate Pulses (d). Note the difference in scale for Temperate Cereals.*

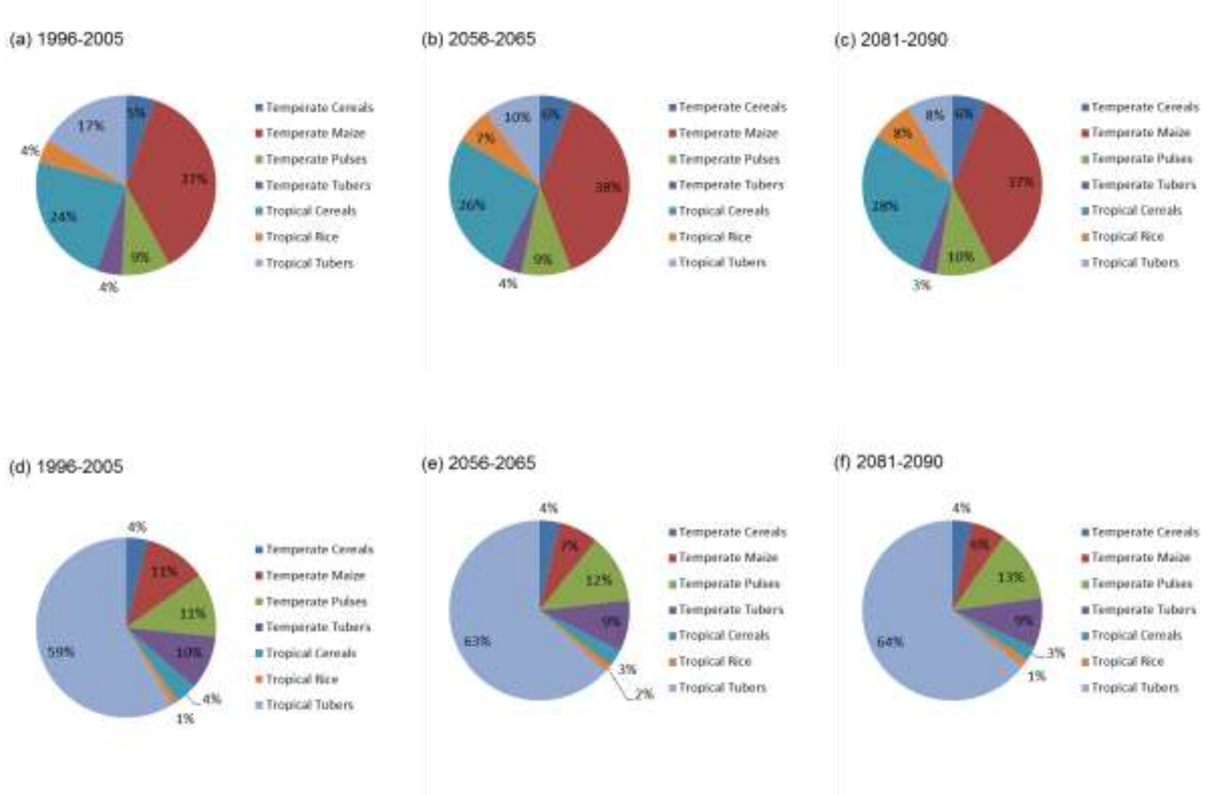

Figure S2. Optimized cropland fractions for the Low Risk (a-c) and High Risk optimization (d-f) for the time periods 1999-2005 (a,d) 2056-2065 (b,e) and 2081-2090 (c,f).

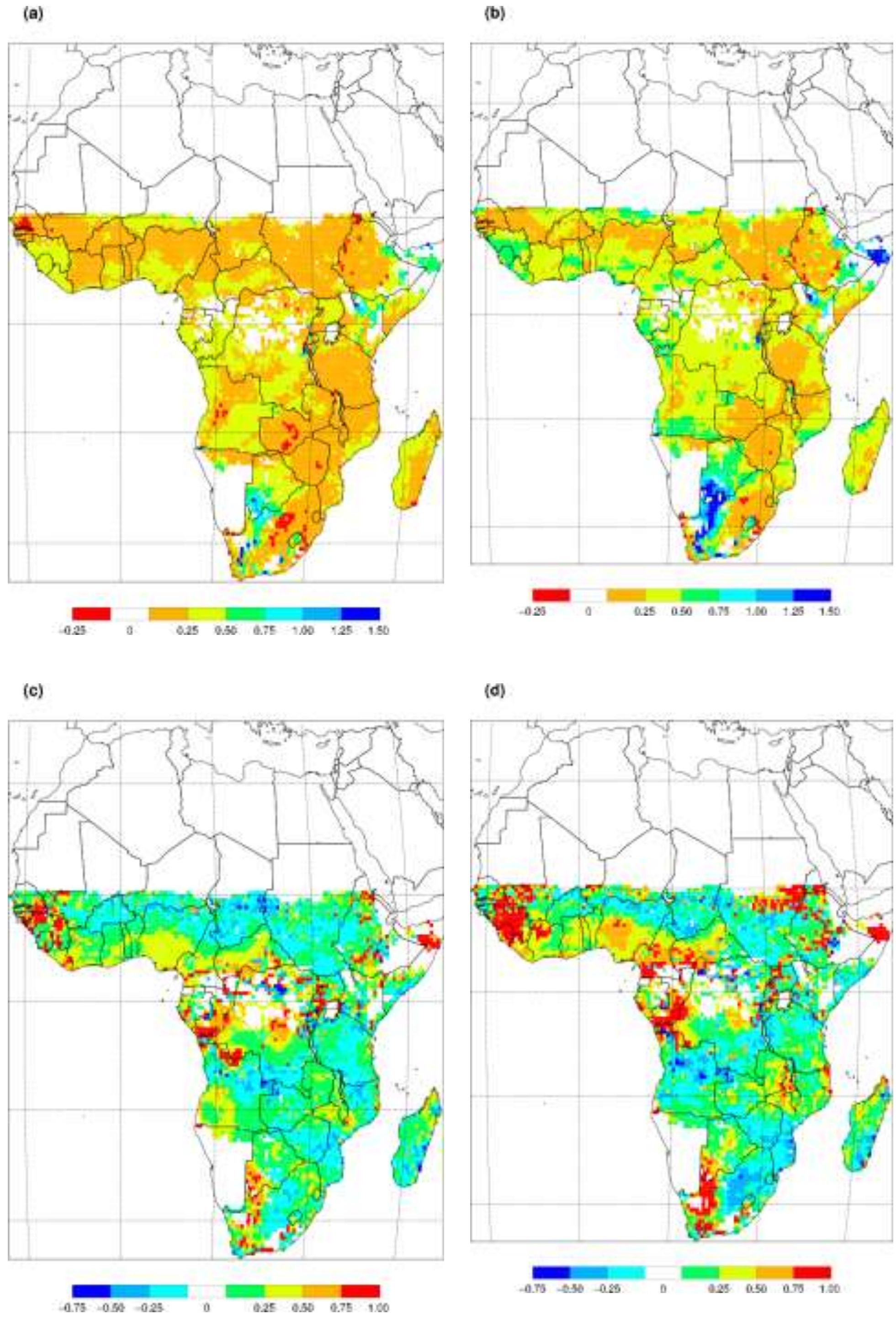

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Figure S3 Relative difference in simulated crop production (a-b) and standard deviation in production (c-d) compared to current climate (1996-2005) assuming current land use fractions (BAU) for both future time periods: 2056-2065 (a and c); and 2081-2090 (b and d).

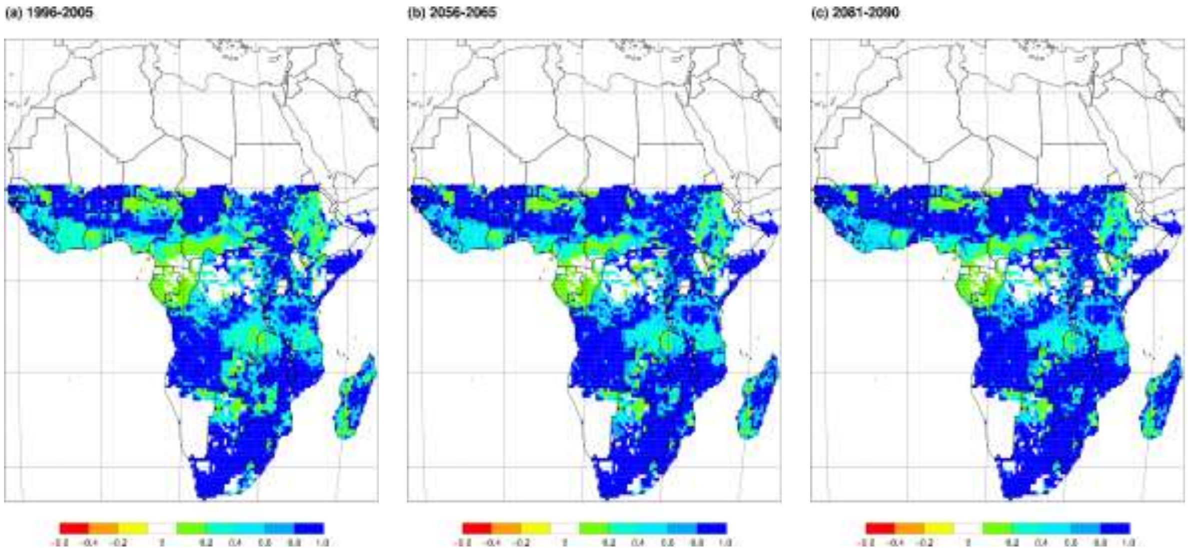

Figure S4. Relative difference in crop production compared to assuming current land use fractions (BAU) for the High Risk optimization, for the years 1996-2005 (a), 2056-2065 (b) and 2081-2090 (c).

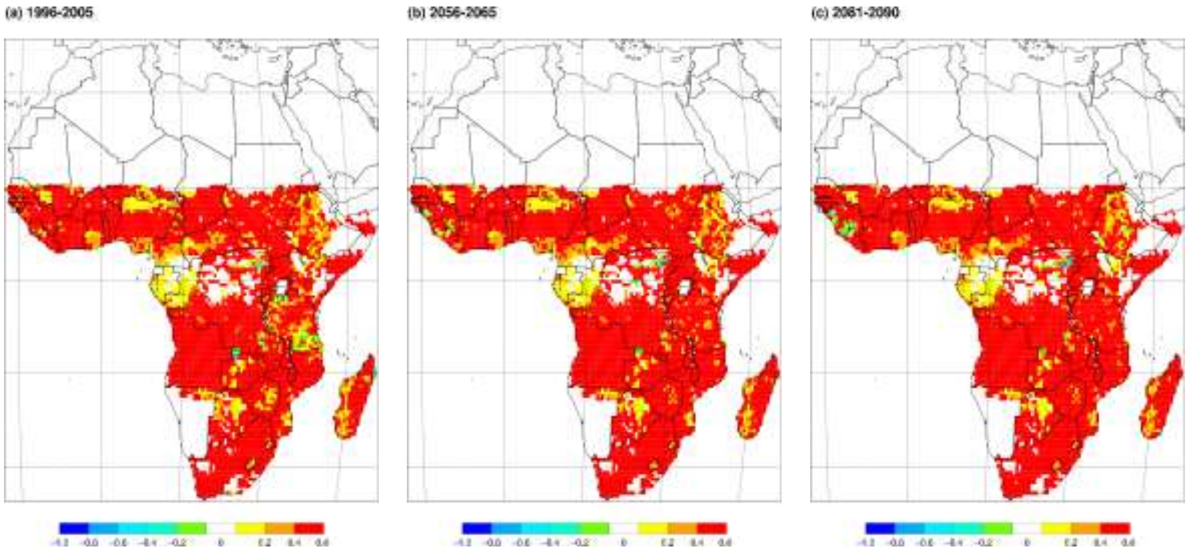

Figure S5. Relative difference in standard deviation in crop production compared to assuming current land use fractions (BAU) for the High Risk optimization, for the years 1996-2005 (a), 2056-2065 (b) and 2081-2090 (c).

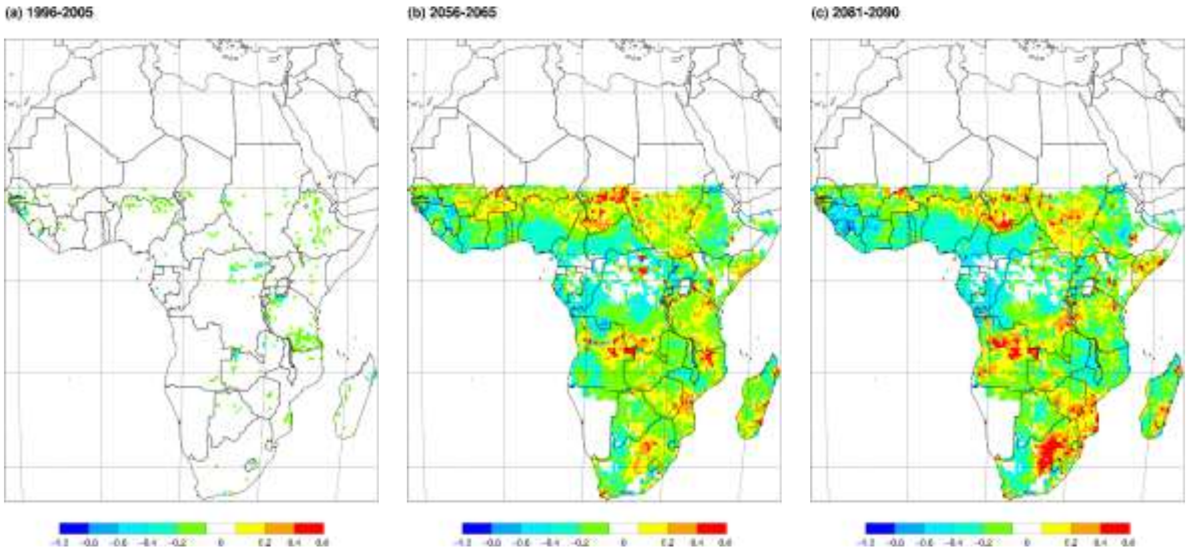

Figure S6. Relative difference in standard deviation in crop production compared to assuming current land use fractions (BAU) for the Low Risk optimization, for the years 1996-2005 (a), 2056-2065 (b) and 2081-2090 (c).

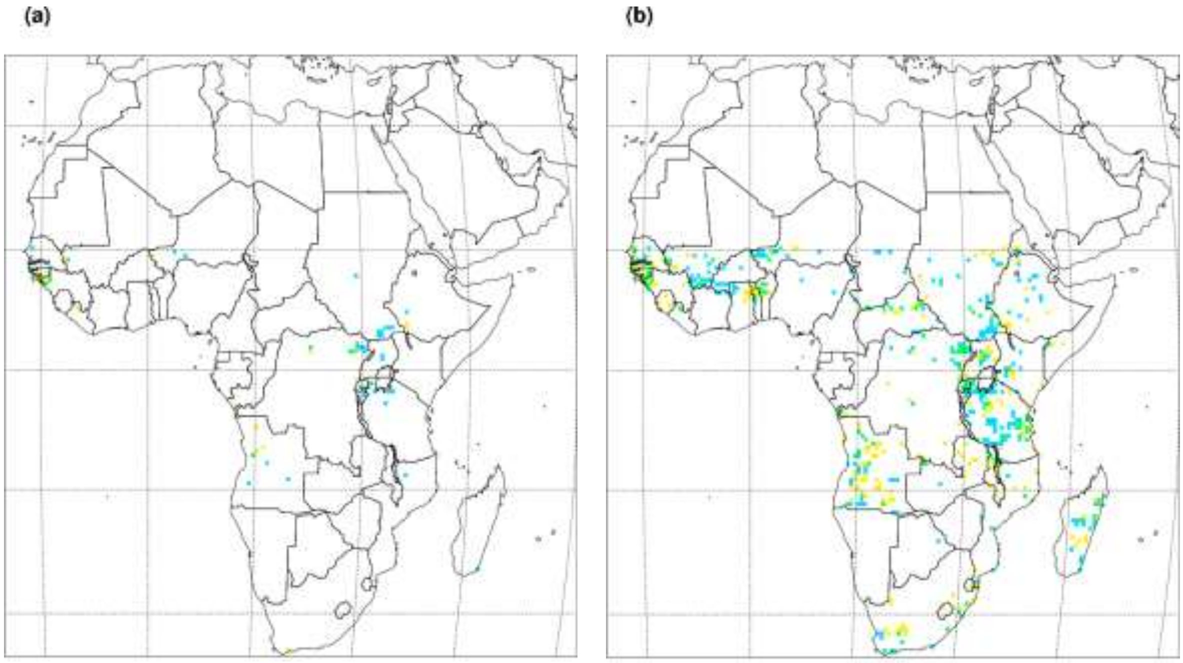

Figure S7. Grid cells where the Low Risk optimization *generated both an increase in crop production and a decrease in the standard deviation in crop production >25% (a) or >10% (b) for the time period 2056-2065 (yellow); 2081-2090 (blue) or both time periods (green).*